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Bridging Data Gaps In The Food Industry – Sensor-Equipped Metal Food Containers As An Enabler For Sustainability

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Abstract

In recent years, Machine Learning (ML) applications for manufacturing have reached a high degree of maturity and can be considered a suitable tool for improving production performance. In addition, ML applications can be used in many other production areas to enhance sustainability within the manufacturing process. One area is storing and transporting bulk materials in metal Intermediate Bulk Containers (IBC). These IBCs are currently used solely for their primary purpose of storage and transportation of raw and finished goods. Hence, while in use, IBCs are often a black box, not providing additional value to manufacturers. Equipping IBCs with sensor technology can provide such value: new data can be generated along the entire supply chain and production processes, taking the sustainability of production to a new level. Within the research project smart.CONSERVE, we use this additional data, for example, to monitor the stored food's critical characteristics or to establish predictive maintenance for IBCs. Thus, storing produced goods in defective IBCs can be avoided, and wasting resources can be prevented. This publication describes how smart IBCs in the food industry can increase supply chain visibility and reduce food waste. To illustrate this, we present possible data-related use cases enabled by smart IBCs, provide insights into how these use cases can be transferred to other industries, and exemplify the many opportunities for manufacturers to develop new smart services and ML applications based on the collected data – and how this can support manufacturers in achieving higher levels of sustainability.

Keywords

Artificial Intelligence; Supply Chain; Sustainability; Smart Solutions; Smart Services; Machine Learning Applications

1. Introduction

In 2008, the global financial and economic crisis strongly impacted industries and supply chain. Despite the economy's recovery in the following years, manufacturing companies in the European Union are still under high competitive pressure [1]. In addition, new products are being launched onto the market with increasing frequency and product life cycles are becoming shorter. This further increases the market pressure on companies [2]. To remain competitive, they have to reduce their production costs [3]. Due to the crises in the food industry over the past decade, such as bovine spongiform encephalopathy, dioxin contamination, rotten meat, classical swine fever, and avian influenza, customers have become increasingly concerned with the quality, origin, and preservation of food [4,5]. Therefore, companies need to regain customers trust. Through a data-transparent supply chain, clients can accurately be informed about product-related information when purchasing food [6]. To gain customers' trust, food enterprises need to increase transparency along the supply chain, as trust is a crucial factor in the food industry [7].

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Nowadays, manufacturing industries face different challenges in the competitive environment – for example, the problems of scheduling and order release – i.e. caused by complex production processes –, inaccurate demand forecasting, and inefficient production. The economic activity of a manufacturing enterprise is to process, refine, and produce raw materials and semi-finished goods [8]. Since food-producing companies fulfill the mentioned factors, they can be considered to belong to the manufacturing industry [9]. We address these challenges in the BMLE-funded joint project "smart.CONSERVE - Smart Container Services for Food Industries". Afterwards the developed smart Intermediate Bulk Containers (IBCs) can be retransferred to other manufacturing branches – as a solution for more data-transparency and enabler for Machine Learning (ML) approaches to increase economic and ecological sustainability within the supply chain.

In recent years, ML applications have become a powerful tool for optimizing performance in various production areas [10]. For example, assisted by ML, decisions or suggestions can be made automatically. Moreover, ML can be used to optimize the scheduling and order release to provide load- and demand-oriented scheduling proposals for production [11]. Furthermore, ML algorithms have been developed for numerous use cases to improve demand forecasting. An example of the relevance of a versatile data basis is the research of [12], proved that the integration of weather forecast data can optimize the demand forecasting for beer. As numerous decisions within the supply chain depend on demand forecasting, more accurate demand forecasts with ML, based on a solid database, can not only decrease the logistic costs but also strengthen customer satisfaction [2,13,14]. Additionally, a suitable forecasting algorithm is an essential element for effective logistic management to maximize the utilization of trucks [1].

In summary, a high level of data availability is the basis for raising the sustainability of many processes connected to the supply chain, by providing smart services that give useful supply chain information based on product- and container-data. In the research project smart.CONSERVE, sensor technology to create data related to stainless steel food IBCs has already been developed but has not been applied in industrial practice, yet. Therefore, this paper aims to answer the following research questions:

- How can existing container fleets be retrofitted with the developed smart technology to provide a sufficient data basis for smart services and advanced ML applications, using various data sources, to increase sustainability in the (food) supply chain?
- How can retrofit scenarios for existing fleets of IBCs be designed without restricting the producer's ability to deliver reliably?
- What are possible ideas for smart services and ML applications to increase sustainability in the food industry by using data collected by smart IBCs?

The remaining parts of this article are structured as follows: section 2 briefly introduces the current use of IBCs for storing and transporting goods, the effects of increasing sustainability requirements, the lack of data, and the challenges for a smart solution in food industries. Section 3 gives an overview of ideas for smart services and ML applications to increase sustainability and reduce food wastage. Section 4 summarizes the technical solution developed in the research project smart.CONSERVE and describes scenarios and challenges for its implementation in existing container fleets. Section 5 offers a conclusion.

2. Initial Situation

The following chapter provides an overview of the initial situation regarding using IBCs within the supply chain and existing ML approaches to increase sustainability within the supply chain in food industries.

2.1 Machine Learning

As in other industries, ML approaches have been developed for the food industry to increase sustainability and competitiveness in various areas of the supply-chain. For example, ML is used to predict the harvest of the coming years [15]. This enables wholesalers to prepare for poor harvests early to gain an advantage over competitors. One approach for reducing food waste is to monitor the evolution of fruit quality in the supply chain after the fruit is harvested. Researchers have developed a method in which a digital twin of the fruit is created at the time of harvest and thermal imaging technologies with ML algorithms are used to monitor the quality of the fruit during storage using the digital twin [16]. In the food industry, ML algorithms are utilized in production planning to minimize overproduction, which often occurs due to process uncertainties that lead to larger production quantities being planned than actual customer demand. To improve production planning, which was previously based on the experience of operators, GARRE et al. developed algorithms that support production planning to minimize the delta and thus reduce the wastage of raw materials [17].

2.2 IBCs in Food Industries

In the industry, reusable IBCs play an essential role. They are suitable for many sectors to transport and store goods, such as beverages, foodstuff, chemicals, or hazardous goods [18]. To meet the diverse requirements, various types of IBCs exist, such as composite, plastic, foldable, heated, and metal IBCs. Because of hygiene, flavor stability, and other food-safety-related reasons, the most common IBC within the food industry is the stainless-steel IBC. For beverages and foodstuff, it is designed to meet the standards of hygiene and flavor stability, to protect the stored goods from being affected by other external factors (i.e. UV radiation) and guarantees the quality of beverages and foodstuffs during transport and storage. Depending on the goods, the IBC can be equipped with additional systems, such as heating or cooling systems [19].

Today, these IBCs are only used to transport and store product materials. There is no collection of product- and container-specific data via sensors in the spirit of a smart IBC. This is due to the strict micro-bacterial safety requirements of the food industry: To avoid product contamination, IBCs have to be completely sealed; hence, no sensor data can be transmitted from the inside via cables. On the other hand, the steel IBC shields the mobile signals to such an extent that direct transmission via mobile network is challenging. As a result, manufacturers have no real-time information about their IBCs and products after leaving the company's warehouse. Consequently, various issues along the supply chain have to be addressed manually by the involved partners, e.g., by phone or email. Following are some examples of these issues identified during guided qualitative interviews with several experts [20]:

- Where are the IBCs and which ones are ready for collection?
- What are the current stock levels of the customers?
- Does the container allow all product-specific storage conditions to be continuously met?

However, with increasing automation in production and logistics planning as well as end consumer demands for a transparent supply chain, the collection of product- and container-specific data are of great importance. The end consumer's need for transparency is underlined by the smart container eZaar, developed for at-home food storage, food stock monitoring, and food wastage prevention [21]. Another call for transparency lies in the fact that IBCs are reused several times. Therefore, IBC owners strive to achieve the highest possible utilization of containers to minimize fleet size and, thus, their capital commitment. However, IBCs are often not immediately reported to the supplier as empty and remain unused in warehouses instead of being reused.

Different from other industries, an essential factor in the food industry is the best-before-date of products, which may not be exceeded and, thus, influences production and warehouse planning [22]. Because of the perishable nature of food, the long lead times for food production, the seasonal variations in production and consumption, and the variability in product quality and yield, the food supply chain has an increased level of complexity [23]. To provide consumers with high-quality fresh products, the planning process for the availability of production capacity and material requirements, the production process, and the distribution planning process must be integrated to ensure on-time product availability [24].

Besides, the strive for ecological and economic sustainability in production is a priority for more and more enterprises [25]. This is motivated by both investor and customer expectations, as well as national and international legislation: In 2015, the Paris Agreement was completed, a treaty under international law with the goal of global climate protection. The adhering countries regularly derive new Nationally Determined Contributions (NDCs) to concretize these goals. [26] As a tool for their implementation, e.g., Germany has been using CO_2 pricing since 2021: This involves pricing CO_2 emissions induced to the use of fossil fuels via a national emissions trading system, currently at 25 euros per ton emitted. Until 2026, the fixed price will gradually rise to 65 euros per ton. After that, the volume of the allowances issued will be limited in line with climate targets, and an auction process will be introduced. [27] This primarily affects industry, which, in Germany, emits 3.5 times more CO_2 than private households [28]. Consequently, the German industry has great potential to reduce CO_2 emissions, but it also faces significant challenges in securing its profitability. The literature describes various starting points for initiating such transformations in production [29]. The highly price-sensitive food industry can address both issues using smart metal IBCs: container fleet sizes and food waste can be reduced. At the same time, transport routes and production processes can be optimized – thus, both economic and ecological benefits for manufacturers and customers can be realized.

To solve these problems, the enterprise Packwise developed a "smart cap" that can be mounted onto plastic IBCs. Through this smart cap, information about the location, fill level, and temperature will be collected, transferred via mobile network, and provided to users via a cloud application. This information can help to track the IBCs, reorder products, and guarantee the quality of the goods. For example, monitoring is required when transporting liquids sensitive to temperature- and pressure- fluctuations and vibrations.

In the research project smart.CONSERVE, this tracking solution for plastic IBCs has been applied to metal IBCs. Several challenges had to be addressed to allow this: Micro-bacterial safety is affected by sensors mounted on the inside of food IBCs; however, outside-mounted sensors can neither measure inside temperature and pressure nor can the steel surface be penetrated by radar to measure the fill level. Besides, mounting the smart cap on the inner side of the lid weakens the mobile signal and, thus, hinders the transfer of the data to the cloud application. The research consortium already elaborated a tracking system solution for metal IBCs to measure the mentioned product-related data [30]. To benefit from these results in industrial practice, metal IBCs have to be equipped with the necessary sensor technology – either involving the container manufacturers during production or by converting existing IBCs. Therefore, the paper outlines approaches and challenges for implementing this sensor technology in industrial practice.

3. Enabling Sustainability with Smart Containers

Smart IBCs can enhance resource usage and sustainability in the food industry, and provide manufacturing companies with the ability to remain competitive during shortages of raw materials and rising energy costs in Europe. As part of the research project, we conducted interviews with various supply chain stakeholders in order to identify innovative use cases. The following is a selection of ideas for smart services and ML applications enabled by container data collection for further research:

- Shelf life monitoring:

  Digital twins can track the product's best-before date in industries with perishable products. On the one hand, this allows customers to be warned in good time before the product's expiration date and to adjust the production schedule. On the other hand, it can also provide complete and secure proof of the shelf life of the ingredients used in production [31]. This way, supply chain partners can optimize resource use and increase end customers' confidence in product quality through traceability.

- Energy optimized storage:

  As described in many publications, the storage temperature significantly influences quality and shelf life [32]. The use of a digital twin combined with a temperature-based best-before profile offers companies the possibility to coordinate storage temperature and production schedule in such a way that the product is consumed strictly within the shelf life. This way, companies can optimize the energy used to cool the products and increase sustainability.

- Automated routing for container collection:

Tracking location, fill level, and shelf life makes it possible to automate the routing for collecting IBCs. There are two input factors for planning the IBCs to be collected. On the one hand, the expiration date can be used to anticipate how many IBCs can be collected on a given day due to an exceeded expiration date. On the other hand, fill level monitoring data (e.g., current fill level and current filling behavior) can be combined with historical data to calculate empty IBCs on a given day using ML. This data can be used with the location of the IBCs to determine the optimal route to pick up the IBCs on a given day using hybrid heuristic algorithms [33]. By improving the capacity utilization of the trucks and optimizing the pick-up route, a reduction in CO2 emissions can be achieved. In addition, the IBC fleet size can be reduced, so less IBCs must be produced and raw materials as well as energy for production can be saved.

- Optimized production planning:

Production planning is essential, regardless of the industry, to produce efficiently, meet customer needs at the right time and be competitive. One key factor in production planning is demand forecasting. For this reason, researchers have been working on optimizing demand forecasting and have developed various heuristic methods and ML algorithms. However, all of these methods rely on data from the supply chain, which is why companies have started to exchange data [34]. The introduction of the developed smart IBCs offers the possibility to implement these new data in ML-based forecasts. Overproduction and, thus, a waste of resources and capital commitment due to planning inaccuracies can be reduced.

Due to the versatile applications for stainless steel IBCs, most of these use cases can be transferred to other industries where IBCs are used to store and transport products (i. e., fluids and granulated substances).

4. Technical approach and practical implementation

In smart.CONSERVE, sensor technology, already used in many applications, has been applied for the first time in stainless steel IBCs, cf. [30]. For example, this involves a pressure sensor, thermometer, accelerometer, brightness sensor, and radar sensor, as well as RFID and GPS. These sensors and technologies allow early warnings in case of temperature- and pressure-related issues, identification of mishandling or improper use, fill-level and thus stock-level monitoring, automatic bookings in ERP systems, location tracking and hence automatic notification of deliveries, inventory tracking as well as route optimization. This technical solution has not been implemented in industrial practice, yet. However, its implementation is necessary to enable the data-related use cases described above.

To enable this implementation in industrial practice, we focused on the development of a concept to equip existing steel IBC fleets of food manufacturers with the developed sensor technologies. This can be part of the production of steel IBCs, which means that food manufacturers can chose between traditional IBCs and smart-enabled food containers. These smart-enabled containers can be used to build up new container management systems or to be embedded into existing ones.

However, qualitative guided expert interviews [20] conducted during the research project suggest that modifying existing steel IBCs and equipping them with smart sensor technology – referred to as "retrofitting" – is the more relevant case for industrial practice and will therefore be focused upon in this paper. Steel IBCs can easily be used for more than 30 years, and food manufacturers usually have a relatively large fleet of containers due to high turnaround times. For individual container fleets, the most feasible retrofitting approach is determined by how many containers are to be equipped with smart technology. Therefore, we explored different retrofitting volumes.

The exploration aimed to define intervals for possible container retrofitting volumes that do not negatively affect process stability and delivery reliability of food manufacturers. These intervals are based on scenarios derived from an ABC analysis on typical order volumes of food manufacturers' customers. This data was generated in the research project smart.CONSERVE. After a manual alignment of the data from different sources, data quality was sufficient to perform an ABC analysis. Based on the results of this analysis and the assumption of a container rotation period of three months per customer, five scenarios could be distinguished. The scenarios can feature full (one scenario) or partial retrofitting (four scenarios) of a container fleet. The partial retrofitting scenarios can be described according to the reference object: On the one hand, partial retrofitting can cover the orders of one or more specific customers ordering from one food manufacturer; on the other hand, partial retrofitting can cover one or more specific products or groups of products, e. g., products sharing one main ingredient. In our ABC analysis, we decided to focus on the "A" category of customers and/ or product orders, i. e., all customers or products needed to reach 80 per cent of the ordered quantity in one representative quarter. In this way, a significant share of customers or product orders can be covered by smart IBCs without the necessity to retrofit entire IBC fleets.

In scenario (1), all IBCs used for supplying one or a small number of customers of a typical food manufacturer are retrofitted. Necessary fleet sizes to cover a "A" customer (as identified in the previous analysis) range from 3,000 to 5,000 containers. To cover the largest customers, fleet sizes of up to 10,000 IBCs would be necessary. Similarly, scenario (2) focuses on the product perspective. To cover the typical "A" product orders from all customers, necessary smart IBC fleet sizes range from 1,500 to 7,000. To cover the most frequently ordered products, fleet sizes of up to 10,000 IBCs would be required. Scenario (3) represents a variation of scenario (2): Retrofitting is limited to the "A" products ordered by "A" customers, requiring the retrofitting of around 2,000 IBCs per "A" customer. In scenario (4), a single product for one "A" customer is chosen, and typically about 1,000 IBCs are equipped. Scenario (5) describes retrofitting an entire fleet of approximately 30,000 containers. Since the above quantities overlap, the described scenarios were synthesized into volume intervals for retrofitting (cf. Table 2). This synthesis was based on one specific finding of our research: If food manufacturers cannot equip their entire IBC fleet with smart technology, it can still be beneficial to either focus on a very specific product and customer, an "A" product and/ or customer, or on one of the three most important products or customers. In the following, the retrofitting process is described and the implications and characteristics of the different volume intervals are derived.

Table 1: Scenarios for retrofitting volumes based on an ABC analysis of customer orders

Scenario	**(1) by customers**	**(2) by products**	**(3) by "A" products**	**(4) one chosen "A" product**	**(5) entire fleet**
Number of retrofitted IBCs	Per "A" customer: 3,000 - 5,000 Total of Top 3 Customers: ~10,000	Per "A" product: 1,500 -7,000 Total of Top 3 Customers: ~10,000	Per "A" customer: ~2,000	Per "A" customer: ~1,000	~30,000

For retrofitting, it is necessary to modify the existing containers: The pre-assembled smart cap has to be mounted on the outer surface of the container lid, the internal sensors on the inner surface. For this purpose, a metal plate is welded to the top to create a flat surface for installing the smart cap. Hooks are welded to the bottom of the lid to hold the sensor package in place. After cooling, a holder for the smart cap is glued to the metal plate. The adhesive has to cure for 24 hours. Metal plates, hooks, and adhesive plates are prefabricated. Hence, in retrofitting, only the lids are modified; the IBCs themselves are not used in this process.

By analyzing typical food production processes during our research, it became evident that all food manufacturers using IBCs must clean and sterilize them before refilling. Usually, the IBCs and the lids are washed separately. This separation during the cleaning process offers easy access to the lids for retrofitting purposes. However, the quantity of available lids for retrofitting is limited by the container rotation period of three months and the characteristics of the washing process itself: as the lids can be washed faster than the IBCs, a possible source for the lids in the washing process is the buffer at the end of the washing line. Lids can be taken from this buffer, retrofitted, and returned to begin the washing process after around two days – due to the necessary curing times of the adhesive. However, only a limited volume of lids can be taken from this buffer without compromising the stability of the washing process and, thus, delivery reliability of a food manufacturer. Based on the conducted interviews with different food manufacturers, we assume this volume to be limited to ca. 50 lids per day. This results in different retrofitting times depending on the quantity category chosen from Table 2. As a result, either internal retrofitting in existing internal maintenance workshops or external retrofitting by a subcontractor or container manufacturer is most feasible. For a small number of containers, an internal retrofit can be carried out in short time. On the contrary, retrofitting 10,000 or more containers requires the contracting of an external company as well as changes to the washing process to increase the daily quantity of modifiable lids – to be able to realize the data-use-related advantages of smart IBCs in a reasonable time frame and to permit internal maintenance workshops to focus on their core tasks. However, these process changes are yet to be determined.

Table 2: Volume intervals for retrofitting

Number of retrofitted IBCs	**< 1,000**	**2000 - 5,000**	**8,000 - 12,000**	**30,000**
(Partly) attainable scenarios	4	(1), (2), 3, 4	1, 2, 3, 4	1, 2, 3, 4, 5
Time for internal retrofitting (days)	< 20	60 - 100	160 - 240	600
External retrofitting	No	No	Optional	Yes

But it is not only the number of removable container lids that is a challenge in the retrofit process. Further challenges in the retrofitting process arise from the different manhole closure types of the IBCs: screw-on lids and bayonet lids. During the filling process of IBCs with bayonet lids, a bell-shaped cover has to be lowered onto the lid for closure. Therefore, the available area for welding the supports for the smart cap and the internal sensors onto the bayonet lids is smaller compared to screw-on lids. This requires a more careful positioning of the supports and the smart cap and makes the retrofitting of bayonet lids more demanding and therefore even more time-consuming. In consequence, this reduces the number of retrofits per day and extends the conversion time of a fleet.

Similarly, not only the retrofitting of the container lids poses a challenge to the stability of the container cycle. Retrofitted containers also require adjustments to their washing process. Additional steps in the disassembly of the containers are the removal of the smart cap and internal sensor package. Extra cleaning is required for the sensor package. After washing, these disassembled parts must be reassembled. While adding new washing process steps is simple in a fully converted fleet, challenges for the washing process arise when it becomes necessary to implement two different washing process variants running in parallel. This can be the case during the retrofitting phase or if a food manufacturer chooses a partial retrofit of its IBC fleet. However, these challenges are not limited to differentiating between two types of containers: partial retrofitting also requires that the washing process allows for order-related washing and buffering at the end of the washing process within the limited space of existing washing facilities. In order to ensure the necessary process stability and thus delivery reliability with smart containers, it is therefore necessary to take into account an exact allocation of the smart containers to the orders in production planning.

Besides, the use of the collected data for food production processes is limited by the percentage of converted containers. Only if a significant part of the fleet is retrofitted, adjustments based on these data can be made in production and supply chain processes. Thus, developing dedicated retrofitting processes for different retrofitting volume intervals is crucial to enable data-related use cases of smart IBCs.

5. Conclusion

Smart metal IBCs have the potential to enable sustainability use cases and ML applications within the supply chain. This work gives some examples for smart services and ML applications enabled by smart metal IBCs. In the smart.CONSERVE research project, a technical solution has already been developed to create the necessary data: the smart cap and the networked sensor package. However, to enable the data-related use cases it is necessary to equip a sufficient number of IBCs with this technical solution. Therefore, the implementation of the developed technical solution in existing container fleets and a retrofit of IBCs is necessary. Our work describes various retrofit scenarios for existing container fleets. Furthermore, the paper highlights the long retrofit time of an entire container fleet as the key problem for enabling smart services and ML applications. It is critical to address this problem to increase sustainability and fill data gaps in the food industry. Therefore, further activities in the current research project will focus on developing a retrofit process in detail, implementing it in a pilot phase and validating the mentioned use cases for data utilization.

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Biography

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